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A methodology for the time-scale-sensitive evaluation of wind speed and direction variability

Cristian Suteanu*

Department of Geography & Environmental Studies / Department of Environmental Science, Saint Mary's University, 923 Robie St., Halifax B3H 3C3,Canada

Abstract

This paper introduces a methodology for the characterization of time-scale-dependent variability in wind patterns. Successive windows of wind speed time series are first analyzed using detrended fluctuation analysis. Isopersistence diagrams are then constructed to reflect the scale-by-scale variability of wind speed over time. Next, wind velocity vectors are projected on a plane that is rotated step by step, and a time-scale-sensitive analysis of the resulting projections is performed for each orientation of the plane, leading to an image of orientation–time-scale–persistence patterns. This methodology is designed to enhance the effectiveness of studies on site-dependent wind variability.

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Keywords: wind intermittency, yaw error minimization, wind farm interconnection, detrended fluctuation analysis, isopersistence diagrams

1. Introduction

Wind energy represents a particularly attractive perpetual energy resource with a low environmental impact. At the same time, it is characterized by strong temporal variability expressed on a wide range of scales. Key objectives involved in wind energy development such as devising new measurement techniques to capture relevant parameters for wind turbine design and siting, extending our knowledge on wind conditions, improving methods for

* Corresponding author. Tel.: +1-902-420-5731; fax: +1-902-496-8213.
E-mail address: cristian.suteanu@smu.ca

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atmospheric processes modeling, and developing better forecasting methods [1], rely on a better understanding of wind patterns. This paper introduces a wind pattern analysis methodology designed to complement existing approaches to wind variability evaluation, focusing on statistical properties of the temporal succession of wind speed and direction values and their relation to time scale.

Patterns in natural time series such as those reflecting wind speed and direction are known to be characterized by high complexity and strong variability; each individual analysis method is only capable of usefully describing some aspects of the pattern, which often makes it necessary to apply multiple approaches to wind data in order to address the range of issues involved in practical questions surrounding wind energy development. Wind speed distributions are among the important instruments used in the evaluations of sites with respect to wind power resources [2]; however, this otherwise effective approach does not capture the temporal succession aspect in wind speed patterns [3]: for instance it does not offer information regarding the probability of occurrence of continuously low wind speed conditions over certain time intervals [4].

Pattern variability is typically expressed on a wide range of time scales, and it may display distinct properties over different temporal scale intervals [5,6]. Evaluating variability as a function of the scale interval represents an important part of data analysis methodologies designed to address pattern uncertainty. Inter-annual variability, with its often strongly localized character, is a particularly valuable component of the assessment framework of energy production scenarios [7]. Yearly values, however, have been found to be insufficient for wind farm site characterization, given the potentially large differences between seasonal and yearly patterns [8]. In fact, seasonal to hourly patterns of wind variability can provide key insights into variability aspects of power availability [9]. Smaller time scales, from minutes to days, are essential to the objectives of improving the quality of resource assessment and integrating different sources of renewable energy [10]. Among the successful methods for the analysis of natural, strongly variable time series, statistical moments – especially L-moments [11] – have been found to be particularly robust and accurate when applied to atmospheric variables. However, they are not designed to grasp pattern features related to the temporal succession of time series values, which are critical to a series of operations dedicated to power availability studies.

Questions that go beyond the insights provided by statistical moments concern relevant aspects of wind patterns such as the persistence of wind speed and the likelihood for increasing (decreasing) speed values to reverse their growing (waning) tendency, as well as the size of wind speed fluctuations and their statistical relationship to time scale. A method capable of meaningfully addressing these questions is useful if it can also reliably handle non-stationary time series. Detrended fluctuation analysis (DFA) [12] fulfills the above requirements. The methodology introduced here builds on the strengths of DFA, incorporating it in a methodological framework capable of accurately depicting time-scale-sensitive properties of the time series, as well as using it in a new procedure designed to assess wind speed and direction variability as a function of time scale. The methodology is exemplified on wind speed and direction data recorded by the AgriMet weather station in Corvallis, Montana, USA, and on Saint Mary's University campus in Halifax, Canada.

2. Methods and results

2.1. Time scale dependence of wind speed variability

In order to address the objectives stated above and effectively characterize aspects of intermittency such as persistence of wind speed values as a function of time scale, taking in consideration the non-stationary character of the time series, we start by applying DFA to successive windows of wind speed time series. DFA has been proven to accurately and comprehensively characterize time series even if trends with unknown sources and shapes are present [12], which can otherwise be the source of biased estimations [13]. The method has been successfully applied in studies concerning a variety of natural time series, including surface air temperature [14, 15]. A brief description of the DFA method is given below (more details regarding this method, the meaning of results, and application examples are provided in [15]).

The analyzed time series window $Q(i)$ is divided in sections of length s. A range of values are chosen for the length s, to span an interval of time scales. The best fit polynomial p of degree N is then found for each section. Different degrees N of the polynomial can be used for this purpose ($N = 1, 2, 3$, etc.), with the degree being specified in the name of the method (DFA1, DFA2, etc.). In this study we apply DFA2; other degrees lead to similar results,

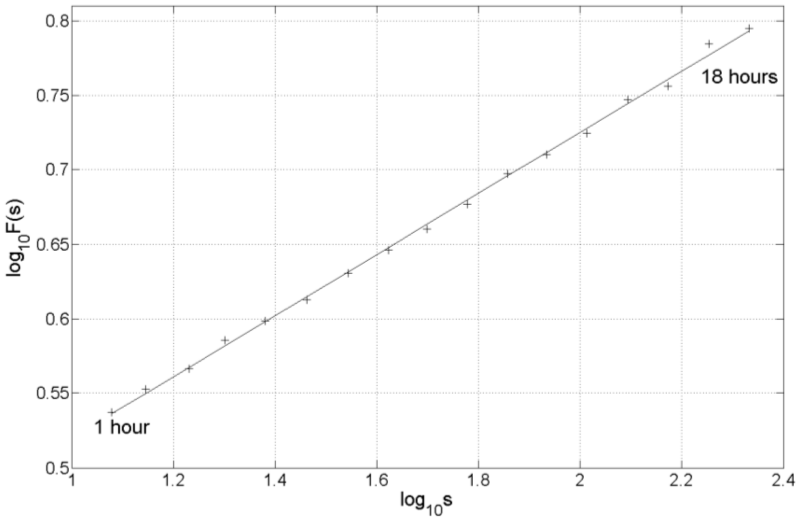

Fig. 1. DFA analysis applied to wind speed time series.

confirming previous studies [15]. The best fit values $p_{m,N}(i)$, where m is the number of the segment, are subtracted from the time series segment of length s:

$$W_{s,m} = Q_m(i) - p_{m,N}(i) \tag{1}$$

and the mean square of the differences between the time series and the interpolation polynomial is calculated for each section m:

$$F_s^2(m) = \left\langle W_{s,m}^2(i) \right\rangle \tag{2}$$

where the angle brackets indicate averaging over all samples in the segment. The square root of the average of these results, $F(s)$, for all the sections of size s is then calculated:

$$F(s) = \left[\frac{1}{r} \sum_{m=1}^{r} F_s^2(m) \right]^{\frac{1}{2}} \tag{3}$$

If $F(s)$ depends on the section length s according to a power law:

$$F^{(N)}(s) \propto s^K \tag{4}$$

then the time series has scaling properties characterized by the exponent K over the scale interval where this relationship holds.

The profile of a random time series (the integrated succession of random numbers) leads to an exponent K=0.5. If $K > 0.5$, the time series is said to manifest persistence, i.e. increasing (decreasing) tendencies are more likely to be followed by further increases (decreases) in time series values, compared to random noise. On the other hand, $K < 0.5$ indicates antipersistence, where increasing (decreasing) tendencies in the values of the time series are more likely to be reversed than in the case of random noise. Wind speed time series typically lead to K-values between 0.15 and 0.30.

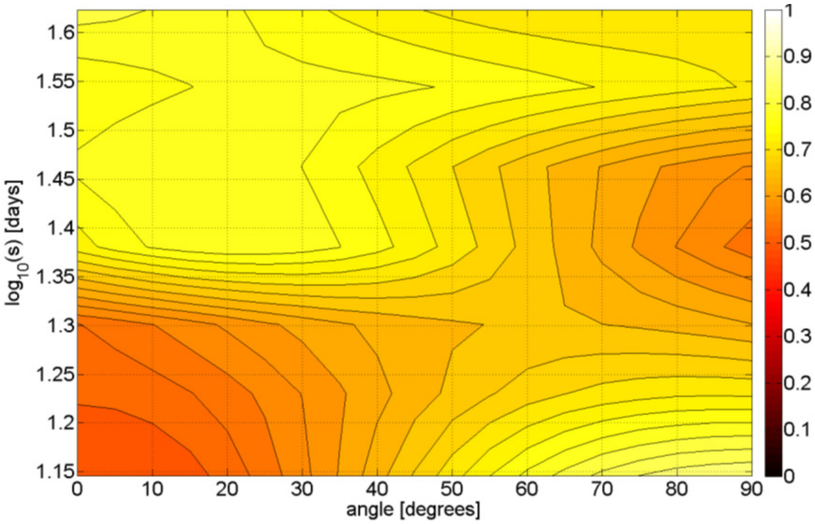

Fig. 2. Isopersistence diagram: the sidebar shows the colour codes that represent the K exponent.

An example diagram illustrating equation (4) is shown in Fig. 1, which refers to a ten day record from Halifax (5 minute sampling). The resulting exponent, $K = 0.21 \pm 0.01$, extends over a time scale interval from 1 hour to 18 hours. The abscissa represents the logarithm of the time scale s in number of samples, while the ordinate shows the size of the fluctuation F determined according to equation (3). The limits of the established time scale interval are also specified in hours in the graph.

The method can be applied to successive windows of time to assess temporal changes in K [16]. Building on this approach, the variability of wind speed vs. time scale and its change over time can be studied by constructing isopersistence diagrams based on DFA analysis. To this end, we start from the recommendation in [17] to determine the scaling properties of suspected power law relations, like the one in equation (4), not only for the entire scale range taken as a whole, but also for successions of scale intervals treated in separation (see Fig. 6 in [18]). However, instead of representing the time scale on the abscissa and the time-scale-interval-dependent exponent on the ordinate, here we turn the representation in that diagram by 90 degrees and show the time scale on the ordinate, while the values of the individual exponents are colour-coded. In this way, the initial diagram is reduced to a single vertical stripe showing the "local" (in terms of time scale) K-exponents represented by a colour for each time scale. Successive windows of the time series are analyzed in the same way, and the results from each of the windows are shown as adjacent stripes, which, together, lead to an isopersistence diagram: this offers a nuanced image of pattern variability, reflecting the scale-by-scale behaviour of the wind pattern and its change over time.

An example is shown in Fig. 2 (15 minute sampling, Corvallis). Successive windows of one month were analyzed over a total time length of four years. The ordinate shows the logarithm of the time scale values in number of samples; the time scale is also shown in hours and days to facilitate interpretation. The blue dots represent the month of January. Instead of producing a graph consisting of one line or a group of lines to reflect the variability in wind speed over time, this approach provides us with a diagram that holds richer information and better insight into the way variability is manifested on different time scale intervals. One can notice that, overall, 16-hour time scales are characterized by less variable persistence than 7 hour or 20 hour intervals, for instance. Persistence change is decreasing with an increase in time scale, until the latter approaches the one day scale. While annual variability is expected, the obtained representation offers a detailed picture of the way in which this occurs: as one can see in Fig. 2, the strongest annual variation is manifested over a time scale range of 1.9 to 2.1 units on the y-axis scale, i.e. a time scale between 20 and 30 hours. For larger time scales, this change in variability is waning.

Diagrams like the one in Fig. 2 can be extended towards shorter or longer time scale values, by using the corresponding segment length values s in the procedure defined by the equations (1) to (4). If one wishes a more detailed graphical representation for certain time scale values, one can take cross-sections in the diagram shown in Fig. 2, and represent the resulting curves in a graph. Alternatively, instead of producing the isopersistence diagram, one can represent the outcome of the described method as a 3-dimensional surface. Rotating the surface around the temporal or the time scale axis, one can consider different perspectives of the variability landscape, to address distinct questions regarding the studied time-scale-dependent dynamics.

This procedure can fruitfully complement other data analysis methods used in studies on wind speed patterns for individual site assessment. Moreover, it can offer rich information to serve as input to models regarding wind farm interconnection: the fact that wind intermittency effects depend on time scale with significant effects for the resulting aggregated power [6] makes a time-scale-sensitive assessment of wind speed variability particularly useful.

2.2. Time scale dependence of wind speed and direction variability

Wind direction patterns can be usefully represented through rose diagrams, especially when the latter reflect wind speed intervals as well. However, this representation does not specify the extent to which wind direction tends to be confined to a certain angle interval for a given length of time, nor does it reflect the temporal change in orientation persistence. Such aspects of wind direction variability play an important role in studies focusing on yaw error minimization, in models concerning wake effects in wind farms, etc. In order to include wind direction information in a time-scale-sensitive variability evaluation methodology, the procedure presented above can be further developed.

To this end, the wind velocity vector recorded for every sample at time t_i, consisting of a wind speed value v and an orientation angle α in the horizontal plane, is projected on a reference direction (Fig. 3). In this way, a projection time series w_i is produced. Next, the whole set of wind velocity vectors in the analyzed window is rotated by an angle δ, and a new projection time series is produced. By repeating this operation, one obtains a set of time series representing projections $w_i(\delta)$.

Each projection is then subject to the DFA analysis procedure described in section 2.1. This time we obtain a vertical slice of an isopersistence diagram for each orientation angle δ, and the resulting diagram will thus have the orientation angle on the abscissa and the time scale values on the ordinate (Fig. 4 shows an example based on wind data from Halifax, 5 minute sampling). The angle δ is chosen as a function of the desired angular resolution (here, δ=2°).

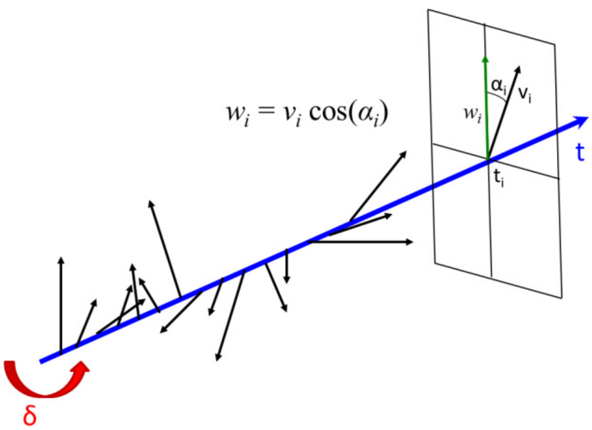

Fig. 3. Generation of wind velocity projection time series

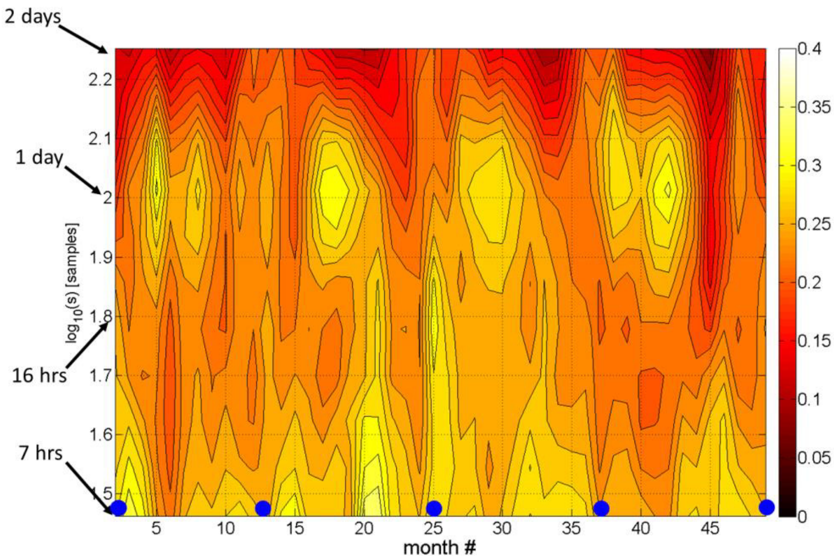

Fig. 4. Diagram representing time-scale-sensitive wind speed and direction variability

The colour bar indicates here again the value of the *K* exponent for each time scale and direction. One can notice in this example time scale range limits separating different types of behaviour in terms of wind speed and direction variability. For instance, an abrupt increase in persistence occurs for direction angles between 0 and 50 degrees, and a drop in persistence is visible for larger angles; the time scale at which this change in persistence occurs is consistently decreasing with growing orientation angle, approximately from 1.35 to 1.28 units on the y-axis scale, i.e. from 95 minutes to 112 minutes in actual time scale. However, for these larger angles persistence is growing with increased angle value over time scale intervals beyond 1.4 units (125 minutes). One can thus explore in detail the tendency of wind patterns to manifest variability over different time scale ranges. The time scale interval in this diagram can also be extended, both towards shorter and longer values, as a function of the purpose of the performed study, by including the corresponding segment lengths *s* in the evaluation procedure described in section 1.1.

3. Conclusions

Wind speed patterns are characterized by strong, scale-range-dependent variability. A time-scale-sensitive analysis method for wind speed patterns is useful for a range of important aspects of site characterization and wind power availability studies. The methodology introduced in this paper addresses the task of characterizing wind speed pattern features from the point of view of their temporal variability as a function of time scale intervals along the desired time scale spectrum.

This methodology starts with detrended fluctuation analysis applied to successive wind speed time series windows, and extends it to build isopersistence diagrams that show the way in which variability evolves over time for each time scale interval of interest. The results support studies concerning the scale-by-scale behaviour of wind speed patterns, providing practically useful information for wind power uncertainty evaluation, and offering valuable input for wind farm interconnection modeling. The methodology presented here also captures wind direction variability with the help of an approach designed to address the local characterization of vector fields. The outcomes offer a detailed picture of wind speed and wind direction patterns as a function of orientation and time scale intervals.

The presented methodology is not meant to replace existing approaches to wind pattern analysis. Given the complexity of such patterns and the spectrum of objectives of wind pattern studies, it is a set of carefully selected methods rather than a single one that we expect to best serve the purpose of effectively addressing questions related to wind power. Therefore, the method introduced here is designed to be part of a toolbox that would include a set of other analysis methods, and to support key goals of wind pattern studies, such as decreasing uncertainties related to wind energy availability and designing systems based on integration of wind farms.

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